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Full Length Research Paper

On-line prediction of tool wears by using methods of artificial neural networks and fuzzy logic

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The goal of this study is prediction of tool wear with integrated system made by on-line monitoring of the changes on tool during cutting operations with using artificial neural networks and fuzzy logic methods. For best monitoring, the tool condition, multiple sensor data are collected to represent the tool condition. Artificial neural networks with different parameters was first trained with sample experimental data and then tested with test data. Fuzzy logic is used for the classification of tool wear which is estimated with neural network according to the predefined levels. Results with 100% accuracy are gained by fuzzy process in predefined classes. The software written for this study can be used to monitor tool condition on-line, saving sensor data, viewing the process on graphic and producing alarm-control signals when it is necessary.

Key words: Tool condition monitoring, artificial neural networks, fuzzy logic, tool wear, turning.

INTRODUCTION

Monitoring of tool condition has been gaining importance in terms of quality of manufactured items and total manufacturing cost. Recent studies show that tool changing time which is not considered for cost saving and efficiency before is now emphasized. In order to avoid dead time and cost of changing unworn tool and to prevent damages that may occur because of using tool which is worn, tool wear must be monitored online.

Direct and indirect methods of measurement are used to realize tool wear (Li, 2001; Lee, 2006; Dimla and Lister, 2000). The direct methods of measurement have not yet proven to be very effective economically nor technically (Jantunen, 2002). Although there are many direct methods of measurement such as optical measure-ment method, radioactivation analysis, measuring distance between cutting tool and workpiece, electrical resistance measurements, measurement of changing workpiece size, each method has disadvantages. Besides, in order to apply some of these methods, cutting process must be stopped (Sağlam, 2000; Savage, 1999).

Wear rate could be determined by indirect methods of measurement during cutting process according to certain parameters of cutting functions. The most common methods are measuring of cutting forces, acoustic emission, sound, and vibration, spindle current and cutting temperature (Sick, 2002; Xiaoli et al., 1997; Varma and Baras, 2002; Chuangwen et al., 2009; Lever et al., 1997). Some of these variable data gained from the system are more related to wear. For instance, cutting forces change during cutting and can be used as an indicator of wear.

Various methods were used for tool condition monitoring (TCM) in the previous years. Mathematical and statistical models were the first two methods applied. Since the variables related to tool condition in cutting process show non-linear characteristics, the models were not succeeded (Lee, 2006). Since artificial neural networks -(ANN) and fuzzy logic (FL) methods are applicable to non-linear problems, by these methods implicit variables regarding tool condition and tool wear could be correlated (Dimla et al., 1997). In case of insufficient and noisy data, the methods can also satisfy instant decision requirement needed for online monitoring of tool

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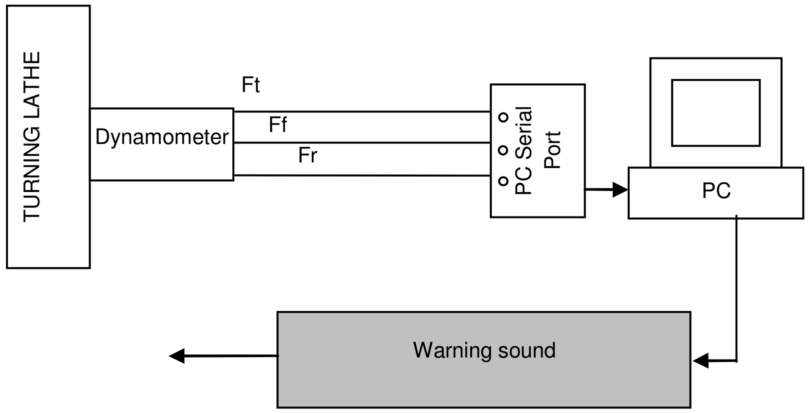

Figure 1. TCM system components.

Table 1. Test groups.

Group no.	Cutting speed (v) (m/min)	Cutting feed (f) (mm / rev)	Depth of cut (d) (mm)
1	260	0,15	1
2	335	0,15	1
3	400	0,15	1
4	335	0,25	1
5	145	0,4	1
6	210	0,4	1
7	260	0,4	1
8	145	0,5	1
9	305	0,5	1
10	335	0,5	1

condition in real time.

In this study, a set-up which estimates tool wear using ANN-FL and produces warning sounds for operator when needed and a software are developed. The software uses Fr (radial force), Ff (feed force) and Ft (main cutting force) cutting forces and cutting parameters v (cutting speed), f (feed), d (depth of cut) as inputs of ANN and creates a “decision making” mechanism. FL is used to classify wear rate according to previously determined level. The tool condition is monitored online, recorded to database to examine data gained by sensors and evaluated.

MATERIALS AND METHODS

A Harrison M300 universal lathe is used for the experiments. AISI 1040 engineering steel Ø45x255 mm in dimension is selected as workpiece. Bohler brand Scmw 09t308 quality ti220 cutting tool is chosen. To measure cutting forces, DKM2000 type dynamometer manufactured by Telc is used. Components of the experimental set-up are illustrated in Figure 1. Main cutting force (Ft), feed force (Ff) and radial force (Fr) data are collected by DKM2000 dynamometer.

The software is written for tool condition monitoring. Whole cutting operation is controlled on-line by this software. The first step is reading force values from dynamometer. This is the data acquisition part of the system. The force values are directly transferred via a cable connected to computer serial port without needing a data acquisition card and an amplifying-filtering process. Then wear value is calculated by using these force values, cutting parameters and trained neural network model. At the same time the software classifies calculated wear values according to predefined fuzzy levels. The last step that the software performs is producing alarm sounds when wear is reached at certain levels. This software works real-time and it is also used for training of the neural network.

Experimental study

In this study, 10 different test groups are formed with constant cutting speed, cutting feed and depth of cut. The values used in these test groups are listed in Table 1.

The software is developed by Delphi 2007 programming language to collect and evaluate the data. The software collects real-time (on-line) data of forces and records them. Moreover, it displays the data of forces graphically and performs the procedure of tool wear prediction and classification applying ANN. The working algorithm of TCM software is shown in Figure 2.

With the experimental set-up, 75 experiments are performed and the cutting force values for each test obtained from dynamometer are recorded. The cutting process is stopped periodically and cutting force values are averaged at each stop from beginning to

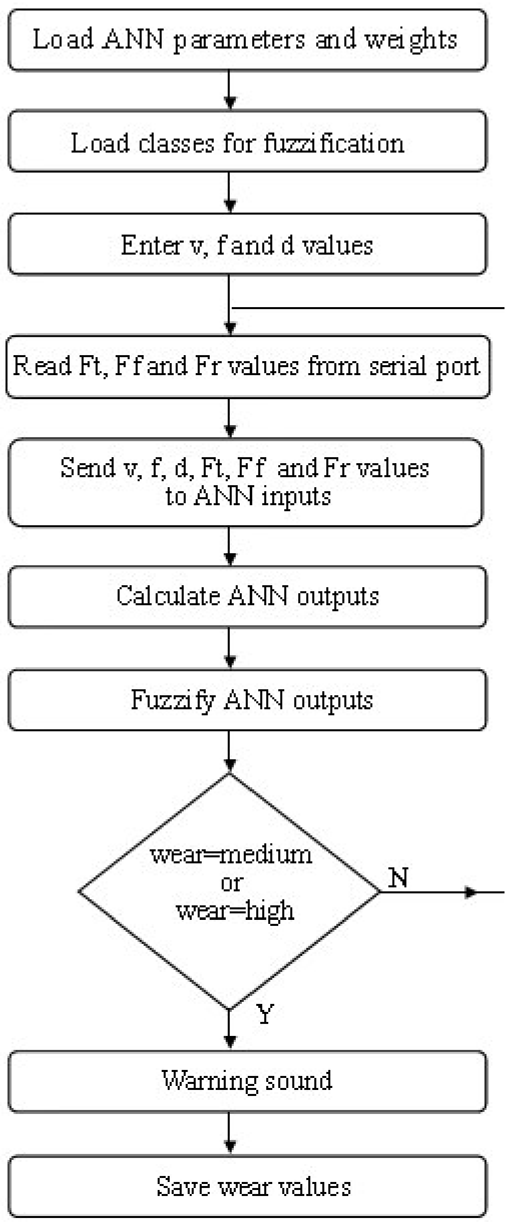

Figure 2. The working algorithm of TCM software.

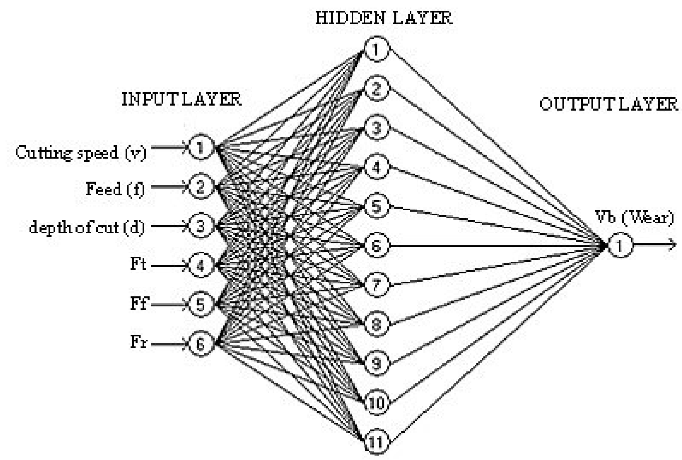

Figure 3. Structure of the ANN model.

that measurement taken at that time. The reason is to prevent the effect of some extreme values of cutting process on calculation. The data gathered are evaluated using ANN inputs and cutting parameters shown in Table 1 and classified according to FL.

The artificial neural network model

The ANN is one of the models used to solve problems by imitating human being. The ANN considers neural cell structure and working principle in human brain. Inputs, weights, summing function, activation function and outputs are the main parts in ANN model (Öztemel, 2003). In this research, commonly used sigmoid activation function is chosen.

Multi layer neural networks are made up of artificial neural network layers gathering together. The network consists of input layer, hidden layer or layers and output layer. In this study, ANN model with feed forward and error back propagation is created. The model is illustrated in Figure 3.

Randomly chosen 80% of data of 75 experiments are saved for educational sample set and 20% of data is used for test set. The sample set is trained by chancing neuron number in hidden layer, learning rate (λ) and momentum coefficient (α) by using the ANN model shown in Figure 3 and the minimum RMSE (root mean squared error) is tried to be reached. The weight values of the ANN model with less square error are used for tests. In order to check whether the model succeeds in unobserved situations, 15 test variables are also used. The number of neurons in hidden layer listed in Table 2 and learning rate-momentum parameters given in Table 3 are used for training with iterations over 100.000.

Fuzzy logic membership functions

In 1965, Zadeh introduced FL and fuzzy sets theory to evaluate uncertainty principle. FL forms a better model of real life. The software created in this study converts values gathered from ANN outputs to expressions in real life. In other words it fuzzifies. The fuzzy expressions of “high”, “medium”, “few” and “too few”” for wear are determined by the aid of experts and the Table 1 in the study (Sick, 2002). The membership functions are given in Table 4 and illustrated in Figure 4

EXPERIMENTAL RESULTS

After training on sample set, data of 15 tests are entered to the network and the performance of network is investigated. In order to measure the success of the network, statistical R^2 method is used. The approximation of the value gained by the method shows how much real values match up with estimated values. Meantime, the TCM software fuzzifies the outputs of the ANN and the software is examined whether it makes a correct classification.

After training, the best result is obtained when RMSE value is 0.029. R^2 value is 0.9877. Learning rate and momentum coefficient are 0.5 and neuron number in hidden layer is 11. Results with 100% accuracy are

Table 2. The ANN model.

Input layer	Hidden layer	Output layer
6 (v,f,d,Ff,Ft,Fr)	3,6,7,8,9,10,11,12,13,14,15,20,30,40,60,3x3,6x6,10x10,20x20,3x3x3,6x6x6, 10x10x10	1 (Vb)

Table 3. Parameters used in ANN training.

λ / α	λ / α	λ / α	λ / α	λ / α	λ / α
0,8 / 0,5	0,5 / 0,5	0,3 / 0,5	0,2 / 0,5	0,1 / 0,5	0,05 / 0,5
0,1 / 0,8	0,1 / 0,7	0,1 / 0,6	0,1 / 0,4	0,1 / 0,3	0,1 / 0,2

Table 4. The Membership functions for wear values.

$$\mu_{\text{High}}(x)=\begin{cases}0 & : \ x<0.4\\ (x-0.4)/0.2 & : \ 0.4\le x\le 0.6\\ 1 & : \ x>0.6\end{cases}$$

$$\mu_{\text{Medium}}(x)=\begin{cases}0 & : \ x<0.2\\ (x-0.2)/0.2 & : \ 0.2\le x\le 0.4\\ (0.6-x)/0.2 & : \ 0.4\le x\le 0.6\\ 0 & : \ x>0.6\end{cases}$$

$$\mu_{\text{Few}}(x)=\begin{cases}0 & : \ x<0\\ x/0.2 & : \ 0\le x\le 0.2\\ (0.4-x)/0.2 & : \ 0.2\le x\le 0.4\\ 0 & : \ x>0.4\end{cases}$$

$$\mu_{\text{Toofew}}(x)=\begin{cases}1 & : \ x<0\\ (0.2-x)/0.2-0 & : \ 0\le x\le 0.2\\ 0 & : \ x>0.2\end{cases}$$

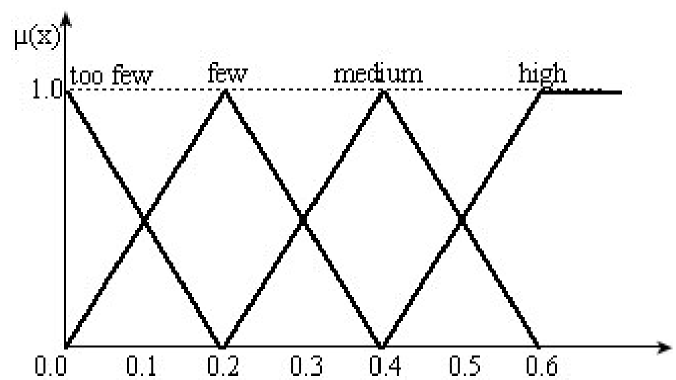

Figure 4. Tool wear membership functions.

Table 5. Comparison of ANN predictions and real values.

Test data no	Wear rate		Fuzzification	
	Real	Predicted	Real	Predicted
1	0.536	0.532	High	High
2	0.457	0.442	Medium	Medium
3	0.152	0.156	Few	Few
4	0.178	0.164	Few	Few
5	0.381	0.358	Medium	Medium
6	0.114	0.104	Few	Few
7	0.368	0.372	Medium	Medium
8	0.089	0.089	Too few	Too few
9	0.368	0.346	Medium	Medium
10	0.165	0.157	Few	Few
11	0.076	0.088	Too few	Too few
12	0.114	0.122	Few	Few
13	0.089	0.071	Too few	Too few
14	0.140	0.110	Few	Few
15	0.419	0.431	Medium	Medium

gained by fuzzy process in pre-determined classes. The comparison of estimated values and real values is shown in Table 5 and in Figure 5 with R^2 trend line.

Conclusions

In this study, ANN and FL methods are examined for monitoring of tool condition in cutting processes. The set-up consists of machine tool. Dynamometer for measuring forces and a computer. The main objective of the study is to determine the tool wear, to examine learning and prediction capabilities of back propagation ANN models. Almost 300 trainings were performed and training error values are analyzed. In literatures, usually root mean squared error (rmse) of the neural network and accuracy (total number of correctly predicted cases / total number of cases) are given to show the performance of the studies. In Table 6. the results of this study are compared to some of the recent researches.

The general conclusions of this study are given below:

1. In manufacturing industry, it is observed that the tool wear is directly affected by cutting parameters and cutting forces and back propagation ANN models are successful in prediction of tool wear.
2. If the number of neurons in hidden layer is two times or more than the number of neurons in the input layer, especially training error and test error values are obtained as small and keeps not changing.
3. Increase in the number of neuron in hidden layer

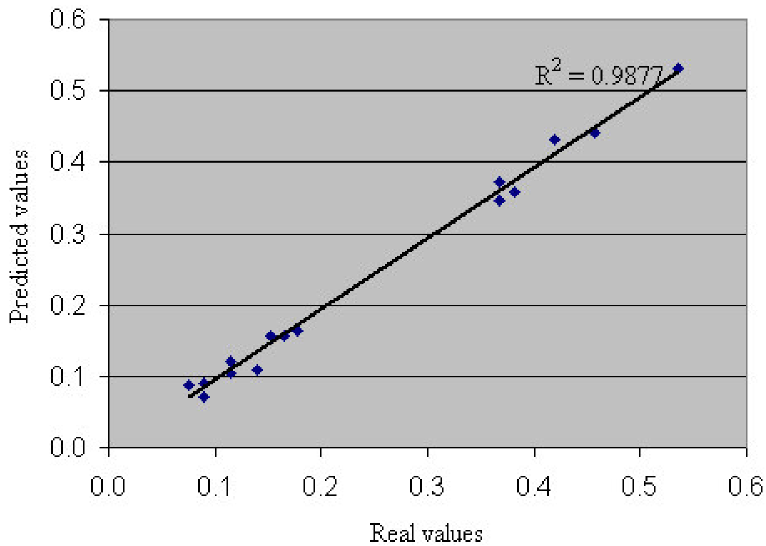

Figure 5. Tool wear performance chart.

Table 6. Comparison of results with recent studies.

Literature	Explanation	Performance metric	Obtained results	Results of this study
Elbestawi et al. (2006)	Vibration and motor power signals are used	Accuracy	93.3%	100%
Li et al. (1997)	AE signals are used	Acuracy	86 - 100%	100%
Dimla et al. (1997)	TCM systems in the literatures are observed	RMSE and accuracy	95 - 100 %	100%
Dutta et al. (2000)	v. f. d and Ft-Ff-Fr are used	RMSE	0.015	0.029
Özel and Karpat (2005)	v. f. tool geometry. Ft-Ff-Fr are used	RMSE	0.021	0.029

causes a decrease in error rate. On the contrary, further increase in neurons leads worse results.

4. More precise results are obtained by using more than one hidden layer but with one hidden layer more approximate results are gained. Similarly, it is observed that the error rate is increased when hidden layer and neuron number in hidden layers are extended further.
5. Increasing of iteration number and maintaining the training do not improve the success of the network. In this study, 100.000 iterations are used and despite of additional trainings the results does not change much in some ANN models.
6. The selection of learning rate and momentum coefficient combination affects the network success and with a momentum coefficient higher than 0.5 the network error is minimized. Besides, it is observed that for better results in low learning rate iteration number must be increased.

The result of this study could be used for researches dealing with unmanned and automated tool changing processes.

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REFERENCES

Chuangwen XU, Zhe LIU, Wencui LUO (2009). A Frequency Band

Energy Analysis of Vibration Signals for Tool Condition Monitoring. Int. Conference Measuring Technol. Mechatronics Automation, 1: 385-388.
Dimla DE, Lister PM, Leighton NJ (1997). Neural Network Solutions to the Tool Condition Monitoring Problem in Metal Cutting-A Critical Review of Methods. Int. J. Mach. Tools Manuf., 37: 1219-1241.
Dimla DE, Lister PM (2000). On-Line Metal Cutting Tool Condition Monitoring Force and Vibration Analyses. Int. J. Mach. Tools Manufacture, 40: 739-768.
Dutta RK, Paul S, Chattopadhyay AB (2000). Applicability Of The Modified Back-Propagation Algorithm In Tool Condition Monitoring For Faster Convergence. J. Mater. Proc. Technol., 98: 299-309.
Elbestawi MA, Dumitrescu M, Ng E-G (2006). Tool Condition Monitoring in Machining. Springer Series in Advanced Manufacturing: Condition Monitoring and Control for Intelligent Manufacturing, pp. 55-82.
Jantunen E (2002). A Summary of Methods Applied to Tool Condition Monitoring in Drilling. Int. J. Mach. Tools Manuf., 42: 997-1010.
Lee SY (2006). In-Process Tool Condition Monitoring Systems in CNC Turning Operations. University of Iowa State. PhD Thesis.
Lever PJA, Marefat MM, Ruwani T (1997). A Machine Learning Approach to Tool Wea Behavior Operational Zones. IEEE Trans. Ind. Appl., 33(1): 264-273.
Li X, Yingxue Y, Zhejun Y (1997). On-Line Tool Condition Monitoring System with Wavelet Fuzzy Neural Network. J. Intell. Manuf., 8: 271-276.
Li X (2001). A Brief Review: Acoustic Emission Method for Tool Wear Monitoring During Turning. Int. J. Machine Tools Manuf., 42: 157-165.
Öztemel E (2003). Yapay Sinir Ağları. Papatya Yayıncılık. İstanbul.
Özel T, Karpat Y (2005). Predictive modeling of surface roughness and tool wear in hard turning using regression and neural Networks. Int. J. Machine Tools Manuf., 45: 467-469
Varma S, Baras JS (2002). Tools Wear Estimation from Acoustic Emissions: A Model Incorporating Wear-Rate. 16th International Conference on Pattern Recognition, 1: 492-495.
Sağlam H (2000). Tool Condition Monitoring Based on Multi-Component Force Measurements Using Artificial Neural Network in Milling. Selcuk University. Graduate School of Natural and Applied Sciences. PhD Thesis.
Savage MD (1999). Multilevel On-Line Surface Roughness Recognition System In End Milling Operation. Iowa State University. PhD Thesis.
Savage LA (1965). Fuzzy Sets. Inf. Control, 8: 338-353.
Sick B (2002). Fusion of Hard and Soft Computing Techniques in Indirect. Online Tool Wear Monitoring. IEEE Transactions on Systems. Man. and Cybernetics- Part C: Appl. Rev., 32(2): 80-91.